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Published in *International Journal of Disaster Risk Reduction* 51 (2020), 101824; doi: 10.1016/j.ijdrr.2020.101824
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Submitted December 24, 2019; revised August 3, 2020; accepted August 21, 2020; published online August 29, 2020.

Perceived Neighborhood: Preferences versus Actualities

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Abstract

Housing recovery plays a key role in the overall restoration of a community. A multitude of factors affect housing recovery, many of which are associated with interactions of residents with their perceived neighborhoods. Targeting perceived neighborhoods rather than administratively defined measures of land helps with devising recovery plans that could better address social preferences of the residents. However, such measures are commonly subject to collection of information via expensive and time-consuming surveys. The current research aims to contribute to the domain by exploring the relationship between perception of households of their neighborhood anchors (perceived anchors) and the anchors that exist within perceived neighborhood boundaries (actual anchors). The goal is to propose a model for classifying households' perceived anchors from publicly available data on actual anchors.

Data were collected on households' attributes, perceived neighborhood boundaries, and perceived community anchors through an online survey of New York and Louisiana residents. Actual anchors were mined from the OpenStreetMap database. Correlation analysis revealed several significant associations between actual and perceived anchors. A multilayer feed-forward neural network model was also developed to predict the classification of households' perceived anchors from actual anchors. Sensitivity analysis of the model disclosed that individuals whose perceived neighborhood comprised more categories of actual anchors were more likely to prioritize infrastructure to other neighborhood assets, a preference that was more dominant in high-density areas.

Keywords: perceived neighborhood, disaster recovery, anchors of social network awareness index, deep learning, feed-forward neural network

1. Introduction

Losses from natural hazards are growing as a result of the increase in number and severity of extreme events and exposure to hazards [1]. Accordingly, a better understanding of recovery dynamics is of vital importance. Among different sectors, housing reestablishment has a ripple effect on overall community recovery [2] because it influences peoples' lives and well-being [3], constitutes the major share of the U.S. building stock [4], and shapes the built environment through households' preferences. Housing recovery is affected by various factors such as households' socioeconomic attributes [5,6], disaster experience [7, 8], level of damage [9,10], social capital [11,12], place attachment [9, 13], recovery of neighbors [14,15], financial aids [16,17], and restoration of community assets [18,19]. Many of these factors—e.g., social capital, place attachment, and reestablishment of community assets—are associated with the interactions of households with their neighborhoods. However, the correct valuation of such variables directly depends on the residents' perspectives toward their neighborhood boundaries. Neighborhoods have traditionally been considered as compositions of individuals and households sharing some commonalities such as origin, history, culture, and values. Neighborhoods contain a sense of relatedness and common risks and benefits [20]. Administratively defined neighborhood units, however, do not consider social characteristics and community constructs. Accordingly, such measures lack the capability of reflecting the potential role of neighborhoods in recovery. Planning for *perceived neighborhood* rather than administrative measures of land can help with devising more effective recovery policies that better address social preferences [21]. Defining neighborhood boundaries through mindset of insiders [22] can provide a more realistic insight into the residents' social interactions and their strategies for maximizing resources and minimizing threats [23].

Recognizing the social characteristics of a community and prioritizing restoration of the perceived anchors, i.e., the community assets that are important to its residents, can substantially improve the overall recovery of the community [24]. The rationale behind this "build it and they will come" strategy is that by dramatically improving one critical piece of a community, the chance of return and recovery of residents would disproportionately increase [25]. Several instances in the recovery of New Orleans and Mississippi after the 2005 Hurricane Katrina demonstrated the effectiveness of this strategy. In the Versailles community, for example, repairing the local church was the first recovery activity. Since the Mary Queen of Vietnam Church historically served as the social and religious center to the Vietnamese American residents, its restoration stimulated the neighborhood's successful recovery. With the same logic, a local health clinic was created in the Lower Ninth Ward neighborhood of New Orleans to help with the return of elderly and lower-income households. Similarly, the Store Manager of a Walmart store in Waveland, Mississippi, took a stance to reopen the store although he had lost his own home in the hurricane. He believed that providing the necessities of life to the families was crucial to the recovery of the community [25–28]. Similar examples were reported after the 2012 Hurricane Sandy in New York where restoration of assets such as schools, stores, and service providers enhanced recovery of the households [29].

However, success of the "build it" strategy heavily relies on the correct selection of critical anchors for reestablishment; a key factor that can be a challenge, especially to non-local leaders. After Hurricane Katrina, the Superintendent of the St. Bernard Parish Public School District, New Orleans, recognized that reopening the educational system was crucial to the overall recovery of the community, as it would accommodate the needs of first respondents for educating their children and would support the long-term future of the society. However, she realized that the state and federal agencies could not assist within the desirable timeframe, as the priority of FEMA, for example, seemed to be protecting endangered species and historic landmarks, and waiting on the Army Corps of Engineers would delay the reopening date. Therefore, in collaboration with the local contractors, portable classrooms were provided from out of state and a 20-classroom school became operational in less than a month. If the superintendent did not have access to the local contractors, restoration of such an important anchor would have likely been delayed [25,28].

Identification and application of perceived anchors as a key to effective recovery is still a missing link in the field of disaster recovery research. Although several studies have researched perceived neighborhood constructs and the factors that influence residents' perspectives toward their neighborhood [23,30–33], their findings could not generally be applied to other areas without recollecting data through expensive and time-consuming surveys. Additionally, while Nejat, Moradi, and Ghosh [34] developed an index (ASNA index) to classify households' perceived anchors, its application needs household-level data on socioeconomic attributes; a high level of resolution that entails either a direct survey or synthetic generation from macro-level data provided by the Census [35]. Therefore, this study intends to bridge the gap by exploring the relationship between households' perceived neighborhood features (perceived anchors) and the features that exist in their perceived neighborhoods (actual anchors). The logic for examining this relationship is that data on actual anchors can be obtained relatively rapidly from publicly available data sources at no cost. The model developed based on this relationship predicts perceived anchors of residents from their neighborhood actual anchors and can help with data-driven identification of community anchors that are most critical to households and their post-disaster recovery decisions.

To do so, data were collected on households' attributes, perceived neighborhood boundaries, and perceived community anchors through an online survey targeting residents of New York and Louisiana. The relationships between the respondents' perceived anchors and actual anchors were evaluated by calculating phi coefficients. Then, a Multi-layer Feed-Forward Neural Network (MLFFNN) model was developed to classify perceptions of households using their perceived neighborhoods' actual anchors.

2. Literature review

2.1. Drivers of recovery

Housing recovery is affected by many drivers and requires a collective effort to be understood [36]. These drivers can be broadly categorized into three groups: internal, interactive, and external drivers [37]. Internal drivers are individual and household-level factors that influence recovery, such as demographic and socioeconomic attributes, experience of past disasters, and level of damage. Socioeconomic status plays an important role in post-disaster recovery. More-advantaged groups are generally able to recover at a faster pace [5,38,39]. Income and employment are other important socioeconomic factors that influence housing recovery [18,40]. Households with greater financial power are more likely to implement predisaster mitigation measures and as a result be less impacted [41], while lower-income populations tend to suffer more damage and experience slower recovery [5]. Race is another demographic factor that can shape the recovery patterns [6]. Racial disparities were reported as contributors to the delayed recovery of New Orleans after Hurricane Katrina [42] and the slow recovery of Miami-Dade, Florida, after the 1992 Hurricane Andrew [5,10]. Marital status [17] and children [43] can also alter recovery decisions, as they differentiate households' priorities. Another factor is education. Dissimilar recovery rates [44] and different priorities [34,43] have been reported for householders with different levels of education. Moreover, households' experience of previous disasters can influence their recovery [45]. Experiencing recurring disasters has been reported as one of the main drivers of residents' relocation decisions [7,8]. For those experienced households who decide to stay and reconstruct, recovery can be accelerated because of their more adaptive behavior [46]. Additionally, the effect of damage is significant and long-lasting [5,47]. Greater damage is associated with a higher relocation rate [9,48] and a prolonged recovery period [6,46].

Interactive drivers of recovery are established and strengthened through the interactions of individuals with their community. Examples of such drivers are social capital, place attachment, and recovery of neighbors. Social capital takes three types: bonding, bridging, and linking [49,50]. Bonding is the connection between similar individuals who often live nearby, such as the relationships between family, friends, and community members who share some commonalities. Oppositely, bridging is the relationship between people with different characteristics, e.g., people from different neighborhoods or ethnicities. While bonding and bridging refer to horizontal relationships among equal individuals, linking is the vertical relationship between people and authorities, i.e., it connects individuals of unequal status and provides them with access to power [51–53]. Social capital can significantly increase community resilience and enhance households' post-disaster recovery [44,46,54]. The recovery of Mano is an example of the positive effect of social capital. Mano is a neighborhood about three miles west of downtown Kobe, Japan. Two-thirds of the Mano houses were destroyed or partially damaged by the 1995 Kobe Earthquake. However, the neighborhood recovered successfully owing to the existing social capital. A sustained trust existed among community members originating from the residents' high participation in various community activities like sports programs, local festivals, and collective decision making (bonding social capital). Further, Mano had a history of interactions with planning consultants, academicians, and neighbors' associations through its past community development activities (bridging social capital). Moreover, interacting with government representatives due to the past development activities had equipped the community leaders with the skills and knowledge of negotiating and dealing with government entities (linking social capital). Consequently, the three forms of social capital collectively helped with the effective recovery of Mano [49]. In contrast, among the coastal villages in Tamil Nadu, India, affected by the 2004 Indian Ocean Tsunami, those without parish councils and communal leadership experienced a delayed recovery. The slow recovery of these neighborhoods was caused partly by the lack of connection with government officials and nonprofit organizations (linking social capital) which could have provided disaster-relief aids [55]. Nevertheless, social capital is a double-edged sword that can cause disparities in the recovery if a community develops more bonding or bonding and linking social capital than bridging social capital. Groups based on only bonding social capital tend to monopolize resources for their members which can disrupt the overall recovery of a community. A megachurch in the River Oaks neighborhood in Houston, Texas, for example, stopped its support of another local and smaller church after the 2017 Hurricane Harvey to help its own congregants, which in turn interrupted the flow of resource to the low-income residents [56,57]. Another interactive driver is place attachment. Place attachment is the residents' loyalty to their place of living developed by place identity and place dependency. While place identity refers to the individuals' perception of identity with respect to the neighborhood, place dependency denotes accommodation of their needs by the neighborhood resources [7,58–60]. Place attachment has been reported to influence recovery of households, for instance, recovery of New Orleans following Hurricane Katrina [13], Rockaway Park, New York [8], and Sea Bright, New Jersey [9], after Hurricane Sandy, and Moore, Oklahoma, in the aftermath of the 2013 tornado [61]. Further, households' recovery decisions are influenced by the recovery of their neighborhood community [15,62] as families tend to rebuild or relocate together [14,63].

External drivers are plans, supports, and services that can help or enhance community recovery, such as financial resources and functionality of community assets. Financial power is an important factor for households' recovery decisions. In addition to the personal financial resources, a household may utilize different types of disaster financial assistance provided by an existing insurance policy or public/nonprofit organizations such as the Federal Emergency Management Agency (FEMA), the Small Business Administration (SBA), and the Department of Housing and Urban Development (HUD). Kamel and Loukaitou-Sideris [16] reported that the regions that had received less assistance in the aftermath of the 1994 Northridge, Los Angeles, earthquake experienced a decline in population and number of residential units. Differently, McNeil et al. [9] proposed that among Sea Bright, New Jersey, residents affected by Hurricane Sandy, those who lacked sufficient financial resources could not afford to relocate and sustain the remaining mortgage and loss of value of their homes. Therefore, many households decided to repair their homes as the only available affordable housing, even for the price of exacerbating their financial situation [9]. In either case, insurance settlements and financial assistance from federal, state, and local organizations play an important role [17]. Additionally, restoration of community assets affects households' recovery decisions. Reopening of businesses, for instance, encourages the neighborhood households to recover, as they can obtain services, goods, and jobs [18,19]. The positive influence of commercial establishments and reopening of businesses on housing recovery has been reported in various cases such as the post-Katrina recovery of the Mississippi Gulf Coast [44], recovery of Galveston, Texas, following the 2008 Hurricane Ike [19], and recovery of New York City in the aftermath of Hurricane Sandy [64]. Restoration of utilities, transportation, schools, and health-care facilities also provide vital services that are required for regular and recovery needs [18,65]. Further, community assets such as faith-based organizations, nonprofit and community-based establishments, social advocacy organizations, and entertainment and recreation centers can amplify the interactive drivers of recovery including social capital and place attachment, which in turn can facilitate the post-disaster recovery efforts [34,44,66,67]. The case of the Versailles community after Hurricane Katrina, for example, illustrates the potential role of faith-based organizations. Versailles Vietnamese showed a successful recovery that was meaningfully different from much of the New Orleans East. The difference resulted from the key role of Mary Queen of Vietnam Church (MQVC). MQVC is the single large public institution in the community and serves as a faith anchor to the Roman Catholic residents who constitute about 80% of the community. Only one month after the hurricane, the church became the center of recovery activities, as the pastor and parishioners returned to begin the recovery process. MQVC served as a shelter to the parishioners and short-term returnees, provided food, assigned specific tasks for repairing houses, administered healthcare activities, facilitated restoration of electricity and water services by communicating with the providers, helped residents with their insurance claims, negotiated with FEMA and the City to open a FEMA trailer park, and collaborated with the other adjacent neighborhoods to oppose the opening of a landfill in the proximity of the community. Therefore, as an important community asset, the church expedited the recovery of households through bonding the residents, bringing them a sense of place attachment, and bridging with other co-ethnic and non-co-ethnic institutions [66–68].

2.2. Perceived neighborhood

Administrative proxies for neighborhood, e.g., census units, have been widely applied because of the availability of associated demographic data [30,32]. However, neighborhoods perceived by residents, rather than administrative boundaries, are the major constituents of social networks and better represent a neighborhood conception [21,31]. While identifying perceived neighborhood and its characteristics is a challenge [69,70], relying on administrative units can bias research outcomes [32,70]. Residents can differ concerning their definition of neighborhood, though they may even live nearby [70]. Therefore, understanding how individuals perceive their neighborhood can significantly help with customizing recovery policies based on the residents' needs and priorities [21,34].

Residents' perception of their neighborhood is influenced by various factors such as sociodemographic attributes, neighborhood characteristics, physical elements, and nearby criminal threats. In the study of low-income communities in ten US cities, Coulton, Jennings, and Chan [31] observed that individuals with longer duration of residence and higher income, education, and engagement in neighborhood activities perceived a larger neighborhood area. Similarly, residents with higher collective efficacy, i.e., with stronger cohesion and mutual trust [71,72], perceived a larger neighborhood [31]. Race and ethnicity also influence the perceived neighborhood. Racial/ethnic similarity or diversity can cause the residents to include or exclude adjacent areas in their perception [23,73]. In a study aimed to assess the needs of Adams County residents in Colorado, researchers found that Spanish-speaking residents perceived larger neighborhoods but identified fewer community assets than their English-speaking counterparts [74]; a dissimilarity stemmed from their cultural differences [21]. Further, among the community assets, public and social services were the most common, and employment and economic development were the least common perceived features [74]. Age, gender, and marital status are of the other socio-demographic factors which influence residents' definition of their neighborhoods [21,33,75].

Further, size of perceived neighborhoods can be influenced by their characteristics. While individuals living in high-density and mixed-used areas may perceive a smaller neighborhood [31], suburban residents tend to have a larger perceived neighborhood area [76]. Physical elements can also affect perceived neighborhood boundaries. People are likely to select the built and natural features, such as streets, parks, and rivers, as the boundaries of their neighborhood [23]. Moreover, fear of criminal threats in the nearby areas, either realistic or overstated, can restrict neighborhood boundaries. Campbell, Henly [23] observed that households exclude the adjacent high-crime areas from their perceived neighborhood. Krysan [73] reported similar behavior; however, the researcher emphasized that the fear in part could be an overinflated perception of crime in communities with specific racial or social class compositions.

Nejat, Moradi, and Ghosh [34] investigated the community features/assets that were deemed important to households' perception of the neighborhood. Referred to these community assets as *anchors of social network awareness*, the researchers applied latent class analysis to develop a new index, Anchors of Social Network Awareness index (ASNA-i), to classify households' perceptions. ASNA indexes households' perceived anchors based on their attributes. The need for developing the index was stemmed from the critical role of interactive and external drivers of recovery, such as neighborhood or transportation facilities, on households' recovery decisions [34]. The analysis revealed three latent classes (index values) linking the respondents' awareness of social anchors to their attributes: Index 1 was characterized by transportation and geographical features, Index 2 was marked by friends and families and neighborhoods, and Index 3 was distinguished by community assets and public services and safety. Accordingly, the indexes were labeled as *infrastructure-aware*, *social-networks-aware*, and *community-assets-aware*, respectively. The outcomes (individuals' indexes) from Nejat, Moradi, and Ghosh [34] were used as input data in one part of the current research, the details of which are explained in the following sections.

3. Research methodology

The following steps summarize the research procedure:

1. Collecting data on households' attributes, perceived neighborhood boundaries, and perceived anchors
2. Determining the actual anchors located within respondents' perceived neighborhood boundaries

3. Bringing in the participants' ASNA indexes from Nejat, Moradi, and Ghosh [34]
4. Examining the relationship between actual anchors and perceived anchors
5. Developing a model for predicting ASNA-i based on the actual anchors

3.1. Online survey

Data on households' attributes, perceived neighborhood boundaries, and perceived community anchors were collected through an online survey of New York and Louisiana residents. The survey was conducted by SurveyMonkey [77]. New York and Louisiana were selected for sample recruitment because of the devastating impact of two extreme events, Hurricane Sandy and Hurricane Katrina, on these states. Data were collected in March and April 2015 from a total of 1368 respondents (556 LA and 812 NY). Polishing the data by removing the duplicate records and missing values resulted in 368 complete records, out of which 231 and 137 records were from New York and Louisiana, respectively.

The survey included three steps. First, the participants were asked about their geographic location of residence, demographic and socioeconomic attributes, and previous experience of a disaster. Additionally, the population density of the county of residence [78] was later added to include a degree of urban-ness. Table 1 summarizes the attributes. Second, respondents were directed to a supplementary website where they were asked to draw a polygon around their perceived neighborhood on Google Maps. Next, they were redirected to the initial website and were asked about the community assets that influenced their perceived neighborhood boundaries, i.e., perceived anchors. These assets were placed into 17 anchors, each representing a specific aspect of a neighborhood's capital (Table 2). More information about the online survey has been provided in Appendix A.

Table 1. Attributes queried in the online survey

Category
State
Population density (log)
Ownership status
Residential status
Gender
Education
Marital status
School-going children living with the family
Race
Employment status
Income
Religion
Personal impact
Property impact

Table 2. Perceived anchors queried in the online survey

Perceived anchor	Abbreviation	Example(s)
Cultural features	PCUL	Museums
Transportation systems	PTRA	Highways and streets
Geographical features	PGEO	Bodies of water, terrain types
Education	PEDU	Schools
Public safety	PPSF	Fire and police departments
Faith-based features	PFAI	Church
Commerce	PCOM	Shopping malls, businesses, banks
Health	PHEA	Clinics and hospitals
Housing	PHOU	Public and affordable housing
Neighborhoods	PNEI	Homeowner association and clubhouses
Nutrition	PNUT	Food banks
Public facilities	PPFC	Libraries and parks
Public services	PPSR	Public works, municipal services, and water tanks
Social services	PSSR	Nonprofit and community-based organization
Employment	PEMP	Job location
Friends and Family	PFRF	Accessibility to friends and family
Others	OTH	

3.2. Actual anchors

Once the survey was completed, perceived neighborhood polygons were mined for the actual community assets existing within the same area using the OpenStreetMap (OSM) database available under the Open Database License [79]. More specifically, 23 tags were of interest of the current study including art center, childcare, college, kindergarten, school, university, fire station, police, church, bank, shop, commercial, clinic, doctors, hospital, pharmacy, cinema, library, shelter, theatre, public, leisure, and drinking water. These community assets were further merged into 8 anchors (Table 3). Operationally, while participants' perceived anchors are those anchors that they listed directly (Table 2), the anchors that are located within their perceived neighborhoods' boundaries represent the actual anchors (Table 3). If a respondent's perceived neighborhood included at least one of the foregoing tags, the corresponding actual anchor was considered to exist within that individual's perceived neighborhood. Labels of perceived and actual anchors of equivalent categories were abbreviated similarly except for the first letter, as *P* represents *Perceived* and *A* denotes *Actual*—e.g., *PCUL* and *ACUL* refer to *Perceived* and *Actual cultural* features, respectively.

Table 3. Actual anchors existing within the perceived neighborhoods

Actual anchor	Abbreviation	Tag(s) in OpenStreetMap
Cultural features	ACUL	Art center
Education	AEDU	Childcare, college, kindergarten, school, university
Public safety	APSF	Fire station, police
Faith-based features	AFAI	Church
Commerce	ACOM	Bank, shop, commercial
Health	AHEA	Clinic, doctors, hospital, pharmacy
Public facilities	APFC	Cinema, library, shelter, theatre, public, leisure
Public services	APSR	Drinking water

3.3. Anchors of social network awareness index (ASNA-i)

Nejat, Moradi, and Ghosh [34] classified residents' perceptions of their neighborhoods into three indexes: Index 1 or *infrastructure-aware*, Index 2 or *social-networks-aware*, and Index 3 or *community-assets-aware*. These indexes were estimated for the present data. The ratio of respondents indexed as 1, 2, and 3 were 47%, 42%, and 11%, respectively, with each index having distinguishably dominant anchors [34]. The estimated indexes were brought in from Nejat, Moradi, and Ghosh [34] to train the model for predicting ASNA indexes from actual anchors.

4. Analysis and results

The association between actual anchors and perceived anchors was evaluated by computing the phi coefficients, which is a correlation coefficient for two dichotomous variables [80]. Dichotomous variables are nominal variables that have only two categories or levels. Perceived anchors and actual anchors are dichotomous variables. For instance, a respondent may have perceived commercial features as *important* or *unimportant*. Commercial features may also be *present* in or *absent* from the respondent's perceived neighborhood polygon. Table 4 presents the cross-tabulation of PCOM and TCOM as an example. According to this table, 17.9% of the respondents perceived commercial features as important anchors, but 83% (14.9 ÷ 17.9) of them actually had such anchors in their perceived neighborhood polygons. On the other hand, commercial features were unimportant to 82.1% of the respondents and these features were absent from perceived neighborhoods of 67% (55.2 ÷ 82.1) of them.

Table 4. Cross-tabulation of perceived and actual commercial features

		PCOM		
		Perceived important	Perceived unimportant	Total
ACOM	Present	14.9%	26.9%	41.8%
	Absent	3.0%	55.2%	58.2%
	Total	17.9%	82.1%	100.0%

The phi coefficients presented in Table 5 indicate that there are several significant or marginally significant relationships between the anchors. For example, while there is not a significant association between actual and perceived cultural features (ACOM and PCOM, respectively), there is a moderate positive relationship between actual and perceived commercial features (ACOM and PCOM, respectively). This means that households whose perceived neighborhood area contains a museum, for instance, may not consider cultural features as their preferred anchors, but households with shopping malls in their neighborhood are likely to perceive commercial anchors as important community assets and vice versa.

Table 5. Phi coefficients

	ACUL	ACOM	AEDU	AFAI	AHEA	APFC	APSR	APSF
PCUL	0.068	0.121	0.161†	0.217*	0.144	0.154	0.045	0.075
PTRA	0.124	0.251**	0.040	0.220*	0.205*	0.004	0.058	0.201*
PCOM	0.188†	0.284**	0.227*	0.258**	0.259**	0.106	0.058	0.334***
PGEO	0.129	0.156	0.114	0.128	0.096	0.257**	0.261**	0.089
PEDU	0.139	0.018	0.240*	0.172†	0.155	0.171†	0.014	0.047
PFAI	0.080	0.012	0.138	0.130	–0.005	0.063	0.045	0.070
PHEA	0.138	0.102	0.137	0.215*	0.232*	0.126	–0.003	0.115
PHOU	0.024	–0.008	0.012	0.197*	0.132	0.042	0.066	0.056
PNEI	0.084	0.008	–0.007	–0.057	–0.048	–0.006	0.144	0.071
PNUT	0.319***	0.203*	0.009	0.061	0.183†	0.001	0.275**	0.086
PPFC	0.066	0.333***	0.277**	0.285**	0.216*	0.209*	0.093	0.153
PPSR	0.031	0.202*	0.124	0.132	0.126	0.113	0.007	0.001
PPSF	0.090	0.092	0.125	0.111	0.071	0.049	0.055	0.089
PSSR	0.319***	0.203*	0.120	0.061	0.183†	0.114	0.275**	0.086
PEMP	0.080	0.169†	0.138	0.183†	0.108	0.123	0.045	0.184†
PFRF	0.063	0.291**	0.103	0.112	0.027	–0.018	0.136	–0.065

Level of significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.1$

Although the above one-by-one relationships between the actual and perceived anchors are informative, many of the relationships are either moderate/weak or insignificant. Besides, estimating a variety of perceived anchors (rather than a classification of them) from the actual anchors might not be much use for planning purposes. As explained previously, the ASNA index classifies households' perception of neighborhood anchors into three classes of infrastructure-aware, social-networks-aware, and community-assets-aware. Therefore, this study aims to establish the relationship between the estimated ASNA index of the respondents and the actual anchors located in their perceived neighborhoods, and then predict a prototypical individual's ASNA index based on a set of actual anchors. Both the response and predictor variables are categorical. The response consists of a label associated with the ASNA index and the predictors are eight binary vectors identifying the presence/absence of the actual anchors located in a perceived neighborhood. Since classification techniques based on a standard generalized linear model usually work well with continuous predictors, this research uses a Multilayer Feed-Forward Neural Network

(MLFFNN). For GLM-based techniques, a link function needs to be posited for connecting the response (or a parameter driving the conditional distribution of the response) to a non-linear function of inputs, Ø(X), a-priori. However, when there is no natural way to select the link function a-priori, it is advisable to identify it based on a data-driven methodology. Hence, deep learning methods, such as multilayer NN, are useful where Ø is learned from a broad class of functions [81]. In the current case, this learning in neural networks is achieved by adjusting the unknown synaptic weights to minimize a preselected cost function [82]. Given the emergence of the multilayer feed-forward neural network as a highly effective classification tool [83], the current study applied this method to demonstrate its applicability in the arena of disaster research.

This paper used patternnet toolbox in MATLAB v. R2019a to create the network. Several networks with different architectures and initial weights were examined to identify the model with the best performance in terms of a small training error and a small gap between training error and generalization (test) error. A small training error ensures that the model does not suffer from the underfitting issue, i.e., it performs well on the data observed in the training. Further, a small gap between training and test errors assures that the model is not overfitted, i.e., it performs well on previously unobserved inputs [81].

The data were randomly divided into training, validation, and test sets with a ratio of 60%, 20%, and 20%. While the training set was used to compute and update the network weights, the validation set was applied to monitor the validation error and estimate the weights associated with the minimum validation error. The test set was then used to calculate the error of the trained network as an independent measure of the model performance. Figure 1 shows the network architecture that achieved the best performance. This model consisted of 4 hidden layers with 6, 4, 6, and 5 hidden neurons (units) in layers 1 to 4. The network employed hyperbolic tangent sigmoid for the hidden layers and softmax function for the output layers.

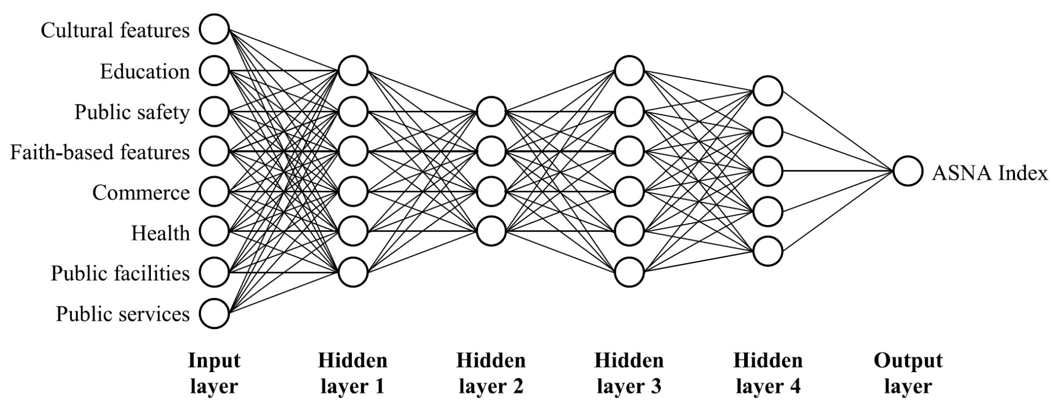


Figure 1. Architecture of the neural network for predicting ASNA indexes from actual anchors.

This setting resulted in the model's training error of 0.224 and a training-test error gap of 0.007. In other words, the model predicted 77.6% of the observed data and 76.9% of the unobserved data correctly, indicating the plausibility of the model's fit to the observed inputs and its generalizability to the new data. Additionally, receiver operating characteristic (ROC) plots were used to evaluate the fit of the network to the data (Fig. 2). ROC plot shows the variation of actual positive and false positive rates on a scale of 0–1. The performance of a classifier is considered better if the curve is closer to (or ideally passes through) the upper left corner, i.e., the area under the ROC plot is larger [84,85]. As Figure 2 suggests, the model has a reasonable performance in training, validation, test, and overall.

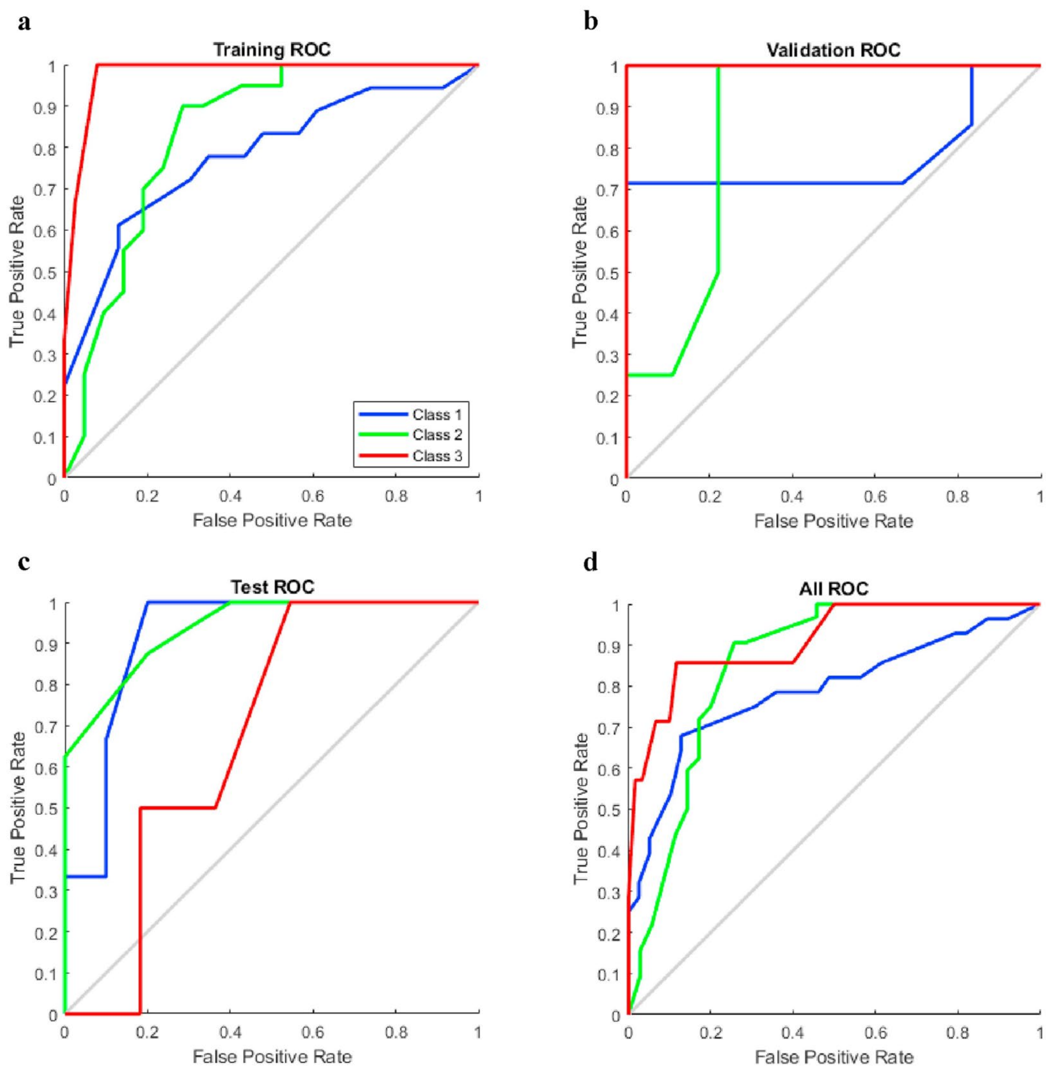


Figure 2. Receiver operating characteristic (ROC) plots of the neural network for (a) training, (b) validation, (c) test, and (d) overall data.

Additionally, the application of the model was examined in hypothetical cases by sensitivity analysis. The objective was to investigate the changes in ASNA indexes with variation in actual anchors located within a perceived neighborhood. To provide the input data, 30 cases were assumed as locations of hypothetical households in New York City (Fig. 3).

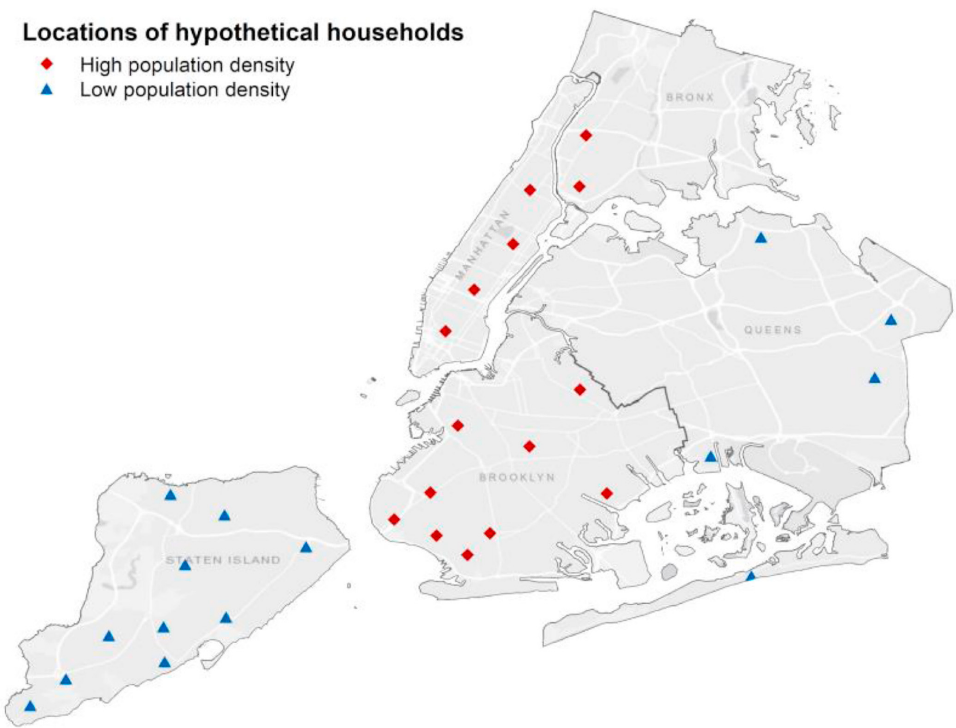
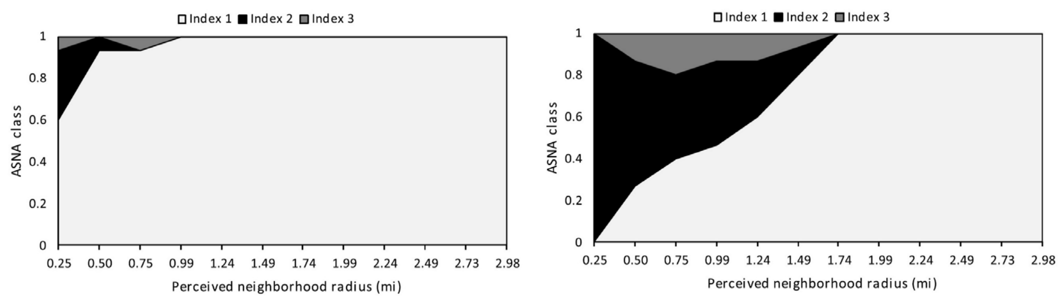


Figure 3. Locations of hypothetical households.

The hypothetical points were distributed with equal probabilities in high and low-population density areas to diversify the neighborhoods' actual anchors. Also, twelve circles centered at each household location were assumed as possible perceived neighborhood boundaries for that household (a total of 360 circles). The smallest circle had a radius equivalent to a 5-min walking, i.e., 0.25 miles or 400 m [86–88]. The radius of each subsequent circle increased by 0.25 miles, giving the largest circle a radius of 60-min walking, i.e., 2.98 miles or 4.8 km. If a circle intersected a significant body of water (e.g., East River), the land on the other side of waterbody was not considered as the current household's perceived neighborhood. The distribution of households' locations and perceived neighborhoods provided the variation of actual anchors required for the subsequent sensitivity analysis. Having the perceived neighborhoods, the community features were found from the OpenStreetMap database and the actual anchors were obtained using a similar approach described previously. Then, the actual anchors were applied as the unobserved input data of the trained MLFFNN model to predict the ASNA indexes associated with the 360 cases (180 cases in high-density areas and 180 cases in low-density areas).

Figure 4 shows the distribution of the ASNA-index memberships predicted for areas with high and low population densities. The results show that in high-density areas, households with a smaller perceived neighborhood area were mostly classified as Index 1 (*infrastructure*-aware), while there were some Index-2 (*social-networks-aware*) and Index-3 (*community-assets-aware*) households. Further, as the perceived neighborhood area grew, all the households were classified as Index 1. The change in the index memberships was slower in low-density areas in which the majority of households with smaller perceived neighborhood areas were of Index 2, *social-networks-aware*, and shifted towards Index 1, *infrastructure-aware*, with the expansion of their perceived neighborhoods.



a) high population density

b) low population density

Figure 4. Distribution of changing ASNA-index memberships subjected to an increase in perceived neighborhood ranges predicted for areas with (a) high population density and (b) low population density.

The patterns observed in Figure 4 were caused by the actual anchors found in perceived neighborhood boundaries; in regions with a higher population density, most categories of actual anchors were found even in a small perceived neighborhood, making the households be classified as Index 1. In lower-density areas, fewer anchors existed within the smaller perceived neighborhood areas which caused different neighborhoods to vary based on the categories of actual anchors included, and therefore, a variety of ASNA indexes showed up. Then again, most anchors were captured even in the low-density areas as the neighborhood size grew which resulted in classifying more households as Index 1.

5. Conclusions

This research aimed to explore how households perceive their neighborhood by examining the relationship between households' perceived anchors and actual anchors existing within their perceived neighborhoods. Data on households' attributes, perceived neighborhood boundaries, and perceived community anchors were collected in March and April 2015 through an online survey targeting residents of New York and Louisiana states. Further, actual anchors located within the perceived neighborhood boundaries were identified using the OpenStreetMap database in April 2019. The relationships between the perceived and actual anchors were explored by calculating the phi coefficients. Then, a multilayer feed-forward neural network model was developed to predict the individuals' ASNA indexes based on the actual anchors. The model correctly predicted 77.6% of the observed data and 76.9% of the unobserved data. Further, the model was applied to explore the changes in the predicted ASNA indexes with the variation of the actual anchors. The sensitivity analysis showed that as the number of actual anchors increased, most households were classified as Index 1, i.e., infrastructure aware. This classification was more dominant in high density areas where many anchors existed even in a small perceived neighborhood.

This research was intended to highlight the importance of perceived neighborhood especially in the context of disaster recovery. While the use of Google Maps API in data collection, extraction of actual anchors from OpenStreetMap database, and developing an MFFNN were of the technical novelties of this research, the major goal was to provide a tool for identifying critical community anchors which their restoration can significantly boost return and recovery of households. Restoration of such anchors has been shown to effectively amplify housing recovery. In post-Katrina recovery, for example, repair of the Mary Queen of Vietnam Catholic Church in New Orleans East, opening the Lower Ninth Ward Health Clinic, and reopening the Waveland Walmart Store considerably advanced recovery of households in the surrounding neighborhoods [25–28]. Similarly, the reopening of schools, shopping centers, and services enhanced housing recovery in New York City after Hurricane Sandy [29].

However, the literature on the social preferences of the residents and its potential application in optimizing recovery plans is still in its infancy. An important challenge is the correct identification of the key anchors since not every community asset holds a position that can be leveraged to improve the recovery of the residents [25]. Anchors perceived crucial in one neighborhood may be different in a nearby neighborhood because of the dissimilar preferences of their residents. Decision makers may also have different perspectives on the importance of various community assets and their recovery priority. For example, while the local authorities in St. Bernard Parish, New Orleans, identified the school as the key anchor for recovery of the community after Hurricane Katrina, federal and state leaders either prioritized other assets or could not be responsive in time [25,28]. Although such issues could be alleviated by gaining insights into the social preferences of a community through surveying its residents, the process of data collection and analysis may not be affordable in many cases especially where time or money is a key factor. The current study, on the other hand, provides a picture of the perceived anchors using publicly available data. The proposed model predicts the influential community assets from a neighborhood's actual anchors; an input that can be obtained relatively fast and free of charge. Once the influential assets are identified, recovery efforts can be directed toward these anchors to help with an effective community recovery.

As with any research, there were limitations associated with this study. One of the limitations stemmed from the nature of online sampling. Despite the growth in accessibility of internet over the recent years, excluding non-internet individuals can cause unbalanced age and gender due to the limited number of the targeted audience. Therefore, one line of future research is to send the survey to a general audience to obtain higher balanced responses and validate the results. Further, as the collected data suggested, boundaries of the perceived neighborhood polygons drawn by the respondents were not influenced by the existence of physical features within the area unlike what has been reported in some literature [23]. Conducting another data collection with more respondents can help to investigate the influence of adjacent elements such as streets and parks on the perception of neighborhood boundaries. Another limitation was caused by the time interval between collecting data on the perceived anchors and actual anchors. While data on perceived anchors were collected through an online survey in March and April 2015, the data on actual anchors were obtained from the OpenStreetMap database in April 2019. Therefore, the anchors found within the respondents' perceived neighborhood polygons in 2019 may be different, at least to some degree, from those in 2015. Therefore, a new survey followed uninterruptedly by querying the true anchors can provide updated data for evaluating the findings and recalibrating the model, if necessary. Despite the limitations, the authors believe that this research has the capacity to help with customizing recovery policies based on specific needs of a given community and making more informed decisions which in turn, can enhance the process of recovery and yield more sustainable and resilient communities [89].

Declaration of competing interest – The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments – This research was supported in part by the National Science Foundation award #1454650 for which the authors express their appreciation. Publication of this paper does not necessarily indicate acceptance by the funding entities of its contents, either inferred or especially expressed herein.

Appendix A. Online survey

Data were collected by surveying the New York and Louisiana residents [21,34]. New York and Louisiana were selected as the geographical boundaries for the survey because of their severe impact by Hurricane Sandy and Hurricane Katrina in 2012 and 2005, respectively. Hurricane Sandy was a post-tropical cyclone that moved onshore near Atlantic City, New Jersey, on October 29, 2012. The hurricane extended in a territory with a diameter of 1000 miles and affected 24 states. Sandy damaged or destroyed 650,000 houses and thousands of businesses and caused 147 casualties and $65 billion in damage [90–92]. Hurricane Katrina touched southeast Louisiana on August 29, 2005, as a Category-3 hurricane and continued in hurricane intensity in the north direction through Mississippi for nearly 100 miles [93]. The hurricane destroyed or damaged 275,000 houses and thousands of businesses and infrastructures [93] and caused 1833 deaths and $108 billion in damage. The severe impact of Katrina placed it as the costliest and among the top-five deadliest hurricanes in the United States [94]. Since the survey was to collect data for exploring households' perceptions and their neighborhood actualities in the context of disaster recovery, it was administered in New York and Louisiana as two hotspots of the disasters to increase the number of participants previously impacted by a disaster. The Office of Human Research Protection Program at Texas Tech University approved the survey. Sample recruitment and data collection were performed by SurveyMonkey [77]. The participants were selected randomly and incentivized by donating 50 cents to their preferred charities and entering sweepstakes. Eliminating a monetary payment and the small amount of donation decreased the potential do-gooders and biases in responses [95,96].

The survey first asked the potential participants whether they were living in New York or Louisiana. Eligible participants were then asked to create an ID by combining their two-letter initials and birthdate (LLMMDD). Next, the participants were asked about their demographic and socioeconomic attributes and previous experience of disaster. Further, the logarithm of population density of county of residence, calculated as the county population divided by its area (square miles), was later added to include a proxy for the urbanness degree. County populations and areas were extracted from the National Association of Counties website [78]. Table A.1 summarizes the data collected in the first step of the survey.

Table A.1. Attributes queried in the online survey

Category
State
Population density (log)
Ownership status
Residential status
Gender
Education
Marital status
School-going children living with the family
Race
Employment status
Income
Religion
Personal impact
Property impact

Third-party tools do not provide micro-level spatial information about the participants [97]. Therefore, a supplementary website was created to collect spatial data on the participants' perceived neighborhoods using Google Maps Application Programming Interface (API). After responding to the attribute-related questions, participants were directed to the supplementary website where they entered their ID and address. Then, they were asked to draw a polygon on Google Maps around their perceived neighborhood. The participants' data collected by SurveyMonkey and through the supplementary website were later linked using their IDs.

After drawing the polygon, participants were redirected to the initial website and were asked about their perceived anchors, i.e., the community features that influenced their definition of perceived neighborhood. Perceived anchors were suggested to the respondents as a list of 17 anchors (Table A.2). Twelve anchors of the list were adopted from an earlier study on mapping Adams County, Colorado neighborhoods in normal settings [74] and five new anchors (transportation systems, geographical features, commerce, friends and family, and others) were added to serve the more specific purpose of this research, i.e., post-disaster recovery. The survey was conducted in March and April 2015 through which data were collected from 1368 individuals (556 LA and 812 NY).

Table A.2. Perceived anchors queried in the online survey

Perceived anchor	Abbreviation	Example(s)
Cultural features	PCUL	Museums
Transportation systems	PTRA	Highways and streets
Geographical features	PGEO	Bodies of water, terrain types
Education	PEDU	Schools
Public safety	PPSF	Fire and police departments
Faith-based features	PFAI	Church
Commerce	PCOM	Shopping malls, businesses, banks
Health	PHEA	Clinics and hospitals
Housing	PHOU	Public and affordable housing
Neighborhoods	PNEI	Homeowner association and clubhouses
Nutrition	PNUT	Food banks
Public facilities	PPFC	Libraries and parks
Public services	PPSR	Public works, municipal services, and water tanks
Social services	PSSR	Nonprofit and community-based organization
Employment	PEMP	Job location
Friends and family	PFRF	Accessibility to friends and family
Others	OTH	

As explained previously, the participants were first asked about their attributes in the SurveyMonkey website, then were directed to the supplementary website to draw their perceived neighborhood boundary, and were finally redirected to the SurveyMonkey website to respond to the perceived neighborhood questions. Quality checks on the collected data revealed that several participants had not responded to some of the questions, not completed the supplementary survey, or not returned to the initial website after drawing their perceived neighborhood boundaries. Additionally, a few records were found to be duplicates, as their respondents' IDs and provided information were identical. Several methods can be used to deal with missing data, such as mean substitution, regression imputation, and maximum likelihood data. However, these methods do not add new information and may lead to inconsistent biases. Case deletion, on the other hand, is by far the most common approach in handling missing data [98]. In the current study, records with missing information were removed from the dataset following the case deletion method. Further, only one case of each set of duplicate cases was included in the dataset. Polishing the data resulted in 368 complete cases, out of which 231 and 137 records were from New York and Louisiana, respectively.

Characteristics of the complete records were compared with the US Census data for two states of New York and Louisiana [99–107] and summarized in Table A.3. In New York, the ratios of homeowners, married, White, and employed individuals were greater in the sample than the population (i.e., Census estimates). The participants also had a higher level of education and income. The ratio of female participants was almost similar in the sample and population. The ratios of participants living in single-family houses and households with school-age children were smaller in the sample. In Louisiana, the ratios of homeowners, female, married, and White individuals and households with school-age children were greater in the sample than the population. The participants also had a higher level of education and income. The ratios of participants living in single-family houses and employed individuals were almost similar in the sample and population.

Table A.3. Comparison of the sample and the population

	New York		Louisiana	
Category	Survey	Census	Survey	Census
Ownership status				
Own	94.8%	53.1%	98.5%	64.6%
Rent	5.2%	46.9%	1.5%	35.4%
Residential status				
Single-family housing	69.3%	77.0%	83.2%	84.2%
Other	30.7%	23.0%	16.8%	15.8%
Gender				
Female	52.8%	51.4%	65.7%	51.1%
Male	47.2%	48.6%	34.3%	49.0%
Education				
High school or less	12.6%	40.5%	18.2%	49.5%
Vocational/Technical/Some College	29.4%	24.5%	32.8%	27.2%
Undergraduate	26.0%	20.0%	31.4%	15.2%
Graduate or Professional	32.0%	15.0%	17.5%	8.0%
Marital status				
Married/Living with partner	72.3%	43.9%	70.8%	43.0%
Not married	27.7%	56.1%	29.2%	57.0%
School-going children living with the family				
Yes	59.5%	76.6%	100.0%	56.5%
No	40.5%	23.4%	0.0%	43.5%
Race				
White	79.7%	63.8%	81.8%	62.4%
Other	20.3%	36.2%	18.2%	37.6%
Employment status				
Employed	74.0%	59.0%	57.7%	55.4%
Unemployed	26.0%	41.0%	42.3%	44.6%
Income				
$49,999 and less	21.2%	42.3%	35.8%	53.1%
$50,000–$99,999	46.3%	28.1%	42.3%	27.2%
$100,000 and more	32.5%	29.6%	21.9%	19.7%

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